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Multi-Dimensional Signal Processing Research Program

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LEXINGTON, MASSACHUSETTS

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FOR THE COMMANDER

Raymond L. Loiselle, Lt.Col., USAF
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MASSACHUSETTS INSTITUTE OF TECHNOLOGY
LINCOLN LABORATORY

MULTI-DIMENSIONAL SIGNAL PROCESSING RESEARCH PROGRAM

SEMIANNUAL TECHNICAL SUMMARY REPORT TO THE ROME AIR DEVELOPMENT CENTER

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ABSTRACT

This Semiannual Technical Summary covers the period 1 April through 30 September 1981. It describes the significant results of the Lincoln Laboratory Multi-Dimensional Signal Processing Research Program, sponsored by the Rome Air Development Center, in the areas of image segmentation and classification, adaptive contrast enhancement, and target detection.

CONTENTS

MULTI-DIMENSIONAL SIGNAL PROCESSING RESEARCH PROGRAM

1. INTRODUCTION AND SUMMARY

The Lincoln Laboratory Multi-Dimensional Signal Processing Research Program was initiated in FY 1980 as a research effort directed toward the development and understanding of the theory of digital processing of multi-dimensional signals and its applications to real-time image processing and analysis. A specific long-range application is the automated processing of aerial reconnaissance imagery. Current research projects which support this long-range goal are image modeling for segmentation, classification and target detection, techniques for adaptive contrast enhancement, and multi-processor architectures for implementing image-processing algorithms. Results in these research areas over the past six months are described in this Semiannual Technical Summary.

Section 2 summarizes the results of experiments with a non-supervised segmentation algorithm. These results were first described in the RADC Multi-Dimensional Signal Processing Program Quarterly Letter Report dated 30 June 1981. Non-supervised image segmentation is a potentially important operation in the automated processing of aerial reconnaissance photographs since it permits the automatic segmentation of an image into regions with similar content.

In Section 3, we summarize the results of recent experiments to enhance aerial reconnaissance photographs degraded by thin cloud cover. Previous work in this area was described in the preceding Semiannual Technical Summary.[1]

During this reporting period, we have begun a preliminary investigation of approaches to the target-detection problem. In Section 4, we describe these approaches and some simple computer simulated results. Automated target detection is an important part of an automated image-analysis system, and we expect that our previous work in image modeling and segmentation will provide a strong foundation for the development of robust target-detection algorithms.

2. IMAGE SEGMENTATION

During the past six months, we have been developing a non-supervised segmentation algorithm based on the supervised segmentation/classification technique developed earlier and reported in Ref. 1. A supervised segmentation algorithm requires training data against which the actual data are compared. Because the training data can be classified, the actual data can also be classified as to type. A non-supervised segmentation algorithm, on the other hand, does not require training data; it segments an image into regions of similar content without classifying the regions into known categories.

During the current reporting period, we have been adapting our supervised segmentation algorithm to work in a non-supervised mode. This is done by using a clustering algorithm to automatically select training data to be used in the supervised segmentation algorithm. The image to be segmented is first broken up into small squares. Then, measurements ("features") are made to distinguish between squares of different texture. Squares of similar texture are grouped together to form a larger square which can be used as training data. Details of this algorithmic approach to non-supervised segmentation are given in the Quarterly Letter Report dated 30 June 1981.

3. ADAPTIVE CONTRAST ENHANCEMENT

In the previous Semiannual Technical Summary,[1] we described in detail several approaches to the problem of reducing the degradation caused in aerial photographs by the presence of thin cloud cover. Several refinements to the previously described enhancement algorithms will be discussed in a forthcoming Technical Report. Here, we shall summarize some of the conclusions of the Technical Report.

Through the use of a simple model to account for the effects of attenuation and contrast reduction due to thin cloud cover, the degraded image can be written as the product of a "signal" term and a "noise" term. Taking the logarithm reduces the product to a sum so that conventional noise-reduction techniques can be applied. If it is assumed that the "signal" and "noise" are stationary random processes, a Wiener filtering approach can be applied.

For images in general, the assumptions of stationarity and randomness are suspect. While certain regions of an image (such as a forested area in an aerial photograph) may be modeled reasonably well as stationary random processes, it is rare that an entire image of interest can be so modeled. Similarly, the effects of the cloud cover, the "noise," may vary across an image and thus be non-stationary. Consequently, we have explored various adaptive techniques based on a deterministic model of images. These techniques operate independently on image sections which are formed by sliding a pyramidal window over the original image. The sections overlap by a factor of two in each direction. Because they operate on the sections independently, these techniques can adapt to changes that occur across the entire image. We have been experimenting with two promising techniques: an adaptive homomorphic algorithm, which applies a variable weighting to the Fourier transform of the logarithm of an image section; and an adaptive highpass filter.

4. TARGET DETECTION

This component of our research relates to the problem of detecting targets in aerial photographs and is a direct outgrowth of our work in image modeling, segmentation, and classification. We can loosely define the target-detection problem as the detection of man-made objects in a textured background (e.g., trees, grass, fields, etc.).

Usually, in detection theory the target (or signal) is added to the background (or noise), and filtering procedures are well established for increasing the signal-to-noise ratio. In image processing, however, the target pixels replace the background pixels. We are currently investigating how this difference impacts algorithms which rely on a difference in intensity and/or variance between the target and the background. A related problem is that of detecting a small target (a few pixels in width) whose intensity and variance do not differ significantly from that of the background, but whose correlation characteristics do. We have focused our efforts on the design of target-detection algorithms for this case.

To facilitate our initial research efforts, we have abstracted the detection problem by modeling the background texture as the output of a linear (and perhaps slowly varying) filter with a white-noise input. More specifically, we assume that output process is autoregressive. A deviation from this model represents the presence of a target in the most general sense. The image model is similar to that used in our image segmentation algorithm. As a consequence, it has led to one particular approach to target detection based on the error or "residual image" of this segmentation procedure.

This modeling approach has also sparked two other methods of target detection. The first is based on a running spectral estimate and a running phase estimate of the background process. The second and perhaps more promising method relies on a recursive least-squares estimate of the background model parameters.

We now outline the three target-detection algorithms which we are currently investigating.

4.1 Residual-Based Detection System

As a by-product of our segmentation algorithm, an "error" or residual image is produced which reflects the amount of information left in the image after the local texture has been removed. Small target-like areas appearing in a texture field should manifest themselves in the residual image since they represent disturbances or "errors" in the underlying texture pattern.

More specifically, it is important that the background residual be statistically white. A target-detection algorithm would then consist of detecting the presence and location of non-white anomalies (e.g., through a chi-squared test) in the residual. Guaranteeing that the residual will be white, however, is non-trivial and has led to some intriguing questions.

In particular, the whiteness requirement implies that the assumed autoregressive texture model must be based on a non-symmetric half-plane filter mask.[2] We have found, however, that to guarantee a white background residual, this mask in general must be of an undesirably large extent, i.e., larger than the target sizes of interest. A typical whitening filter (based on a field-type texture obtained from an aerial photograph) is shown in Fig. 1. Thus, we have

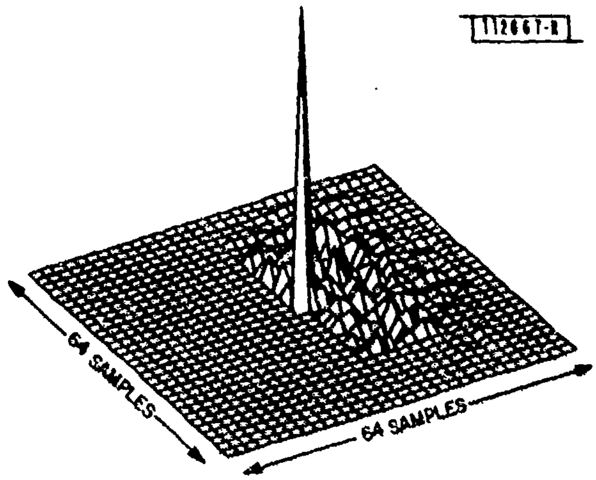

Fig. 1. Typical non-symmetric half-plane whitening filter.

what might be called a "whiteness-resolution" trade-off. Another potential problem with this approach is that the model makes an implicit assumption of stationarity. Clearly, for real-world images, this assumption is questionable. A third potential problem with this approach is that the magnitude of the residual error tends to be sensitive to the intensity of the target (e.g., a low-intensity target will generate an error of small magnitude).

Nevertheless, although we have gained some important theoretical insights into the nature of the use of the residual, we have only touched the surface. For example, Willsky's work[3] in detecting abrupt changes in non-stationary systems may very well be applicable and, moreover, help defeat the resolution limitations imposed by the size of the whitening filter.

4.2 Target Detection Based on Sliding Spectrum and Phase Estimates

In this technique, we compute (assuming the same model as before) the periodogram of the signal under a sliding finite-extent window and compare this spectral estimate with the true spectral density. More specifically, we denote the sampled periodogram at some time m by $S_m(k)$ and the sampled true spectral density by $S(k)$. (For simplicity, our analysis has been applied to 1-D signals.) We then form an error function of the form

$$E(m) = \sum_k |S(k) - S_m(k)|^2 \quad . \tag{1}$$

The basic idea is that, when a target lies under the analysis window, E(m) will increase in magnitude. Peaks in E(m) should then indicate the presence of a target. An example of this procedure applied to a 4-point target is illustrated in Fig. 2(a-c), where a threshold is applied to E(m) resulting in detection of three of the four target points.

One apparent problem with this approach is that $S_m(k)$ tends to reflect local changes in variance and mean level which do not reflect changes in "texture" characteristics (i.e., the actual model parameters). One procedure which seems less sensitive to such variations is to first convert $S_m(k)$ to a "phase" function. In particular, we have applied the Hilbert transform to the $\log|S_m(k)|$, producing a (minimum-phase) phase function which is less sensitive to DC or scaling changes in the original signal. An example, using a mean-squared error function based on this running phase function, is demonstrated in Fig. 3(a-b), where it is shown to obtain a better estimate of the target location than that from the running periodogram.

Of course, since these methods rely on knowledge of the background spectrum S(k), they may fail in distinguishing between a slowly varying non-stationary background and a target. It might be prudent to modify E(m) to be independent of S(k) by using a difference of the form $S_m(k) - S_{m-1}(k)$. Such a difference may change radically only when anomalies in the data appear. We are currently investigating this modified approach.

4.3 Target Detection by Recursive Least-Squares Filtering

In essence, the recursive least-squares algorithm "tracks" the model parameters of the background. When a target area is reached, the parameters tend to change quickly, indicating the presence of a target. This approach is similar in style to that of Dove and Oppenheim,[4] but is applied here to stochastic, rather than determini 'ic, pulse-like signals. Since this approach appears at present to be the most promising of our detection schemes, we shall expend some effort in describing the algorithm.

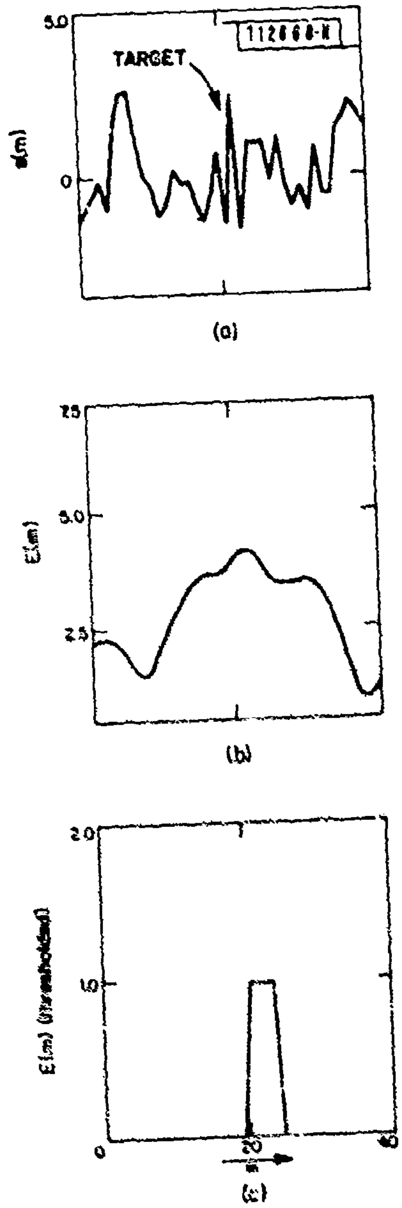

Fig. 2. Detection of a 4-point target with sliding periodogram: (a) a sequence s(m) representing background and target, (b) error function E(m) in Eq. (1), and (c) result of thresholding E(m) in (b).

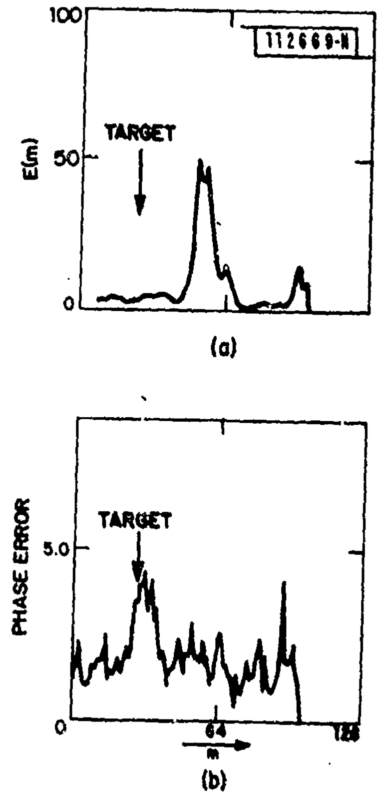

Fig. 3. Comparison of use of sliding periodogram and sliding phase for detection of a 4-point target: (a) error function E(m) in Eq. (1), and (b) error function corresponding to sliding phase function.

Let us suppose that a 1-D sequence s(n) is generated by a difference equation of the form

$$s(n) = \sum_{k=1}^{P} a(k)\, s(n-k) + w(n) \tag{2}$$

where w(n) is white noise. The objective is to estimate the model parameters a(k) for $k \in [1, p]$ from s(n). Further, let us suppose that we have available a segment of s(n) for n in the interval $[-p + n_0, n_1]$, that is, $n_1 - n_0 + p + 1$ data points. We then define the error e(n) over the interval $[n_0, n_1]$ by

$$e(n) = s(n) - \sum_{k=1}^{P} a(k)\, s(n-k) \qquad n \in [n_0, n_1] \quad . \tag{3}$$

The goal is to minimize the sum of the squared errors given by

$$E[n_1] = \sum_{n=n_0}^{n_1} e^2(n) \quad . \tag{4}$$

Performing this minimization (either through differentiation or the projection theorem), we find a set of coefficients which will be denoted by the vector $\hat{a}[n_1]$.

If a new data point is given, i.e., $s(n_1 + 1)$, and an old one is eliminated, i.e., $s(n_0 - p)$, then the new data set runs from $n_0 - p + 1$ to $n_1 + 1$. Clearly, there is much redundancy between the old and the new data sets. This redundancy motivates a recursive scheme for generating the new from the old coefficient estimates. This recursive algorithm can be shown to be given by

$$\hat{a}[n_1 + 1] = \hat{a}[n_1] + G[n_1]\ (u[n_1] - v^t[n_1]\ \hat{a}[n_1]) \tag{5}$$

where t denotes transpose, $u[n_1]$ and $v[n_1]$ are two matrices depending on the new and the old data sets, and $C[n_1]$ is a gain matrix which is easily and recursively updated.

Equation (5) closely resembles the recursion associated with Kalman filtering. In fact, viewing the coefficients $\hat{a}$ as states, under certain conditions, RLS filtering is equivalent to Kalman filtering.[5]

One way of judging the performance of the recursive estimate Eq. (5) is to investigate the mean-squared error between the known coefficients and the estimates:

$$A[n_1] = (a - \hat{a}[n_1])^t\ (a - \hat{a}[n_1]) \quad . \tag{6}$$

After an initial transient, $\hat{a}[n_1]$ should move toward a as long as the signal obeys the model. If the signal suddenly deviates from the background because of the presence of a target, the error $A[n_1]$ should suddenly change to account for the large error that would be encountered in trying to predict the first few points of the target if $\hat{a}[n_1 + 1]$ didn't change much from $\hat{a}[n_1]$. As we shall see, this is indeed what happens.

Of course, Eq. (6) relies on a priori knowledge of the statistics of the process s(n) (i.e., the background). To free ourselves from such requirements, we might consider an alternate performance measure of the form:

$$C[n_1] = (\hat{a}[n_1 + 1] - \hat{a}[n_1])^t\,(\hat{a}[n_1 + 1] - \hat{a}[n_1]) \quad . \tag{7}$$

A similar error was considered by Dove and Oppenheim[4] who referred to Eq. (7) as the coefficient change error.

With a bit of intuitive reasoning, we expect that $A[n_1]$ will increase when the sliding window first "hits" the target. It will stay high as long as the target lies under the window, and then should fall when the target no longer falls under the window. It is reasonable then to filter the data in the opposite direction and multiply forward and backward errors to form a new error criterion. The resulting error should be high over only the target's extent. If the same procedure is applied with $C[n_1]$, we expect the resulting error to be high only at the locations of the first and last target points.

One method of extending this algorithm to 2-D is to apply RLS to each row (or each column). Of course, such a procedure is not "optimal" since the correlation of a 2-D sequence s(n, m) is considered in only one direction, thus apparently reducing the effectiveness of the algorithm.

As before, we might consider an error formed from the product of forward and backward errors (along rows or columns). With $A[n_1]$ the target outline should be filled in, while with $C[n_1]$ only the target boundary (in one direction) should be evident. We are currently pursuing this extension to 2-D.

Consider now an example in 1-D where a background is generated by the first-order difference equation given by

$$s(n) = 0.9\, s(n-1) + w(n) \tag{8}$$

and a target which replaces s(n) over some small interval is given by

$$g(n) = -0.9\, g(n-1) + w(n) \qquad \text{for } n \in [m_0, m_1] \tag{9}$$

where w(n) is white noise.

To demonstrate the sensitivity of the RLS algorithm to small targets, we incorporate first a 4-point and next a 1-point target within s(n). A 20-point sliding window, the correct model order, and $A[n_1]$ were used in these 1-D examples. Figures 4(a-d) and 5(a-d) illustrate the performance of the algorithm in these two cases.

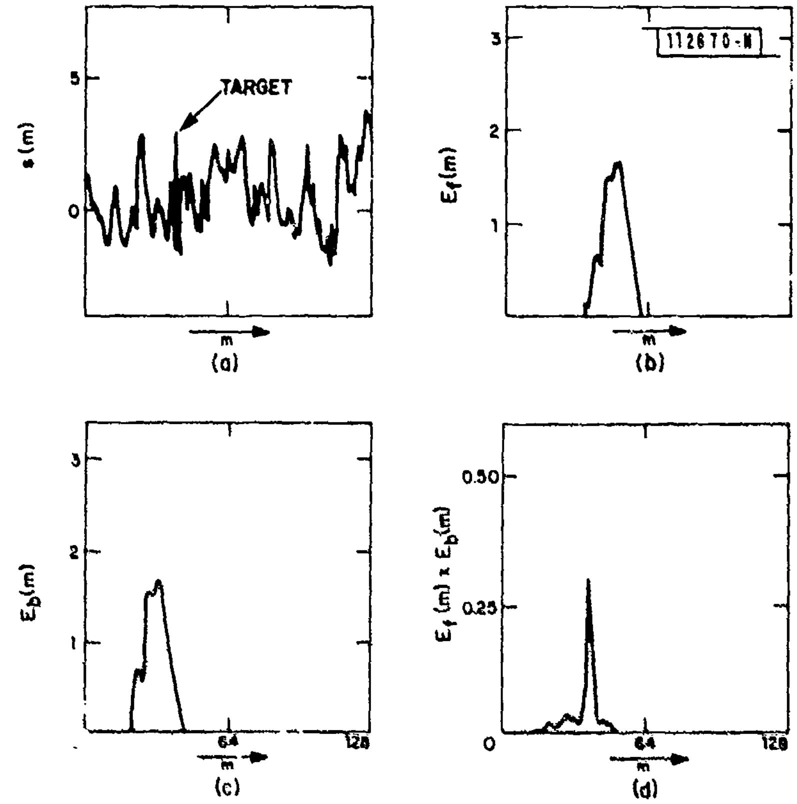

Fig. 4. Detection of a 4-point target by RLS: (a) a sequence s(m) representing background and target, (b) forward error [denoted by $E_f(m)$], (c) background error [denoted by $E_b(m)$], and (d) product $E_f(m) \times E_b(m)$.

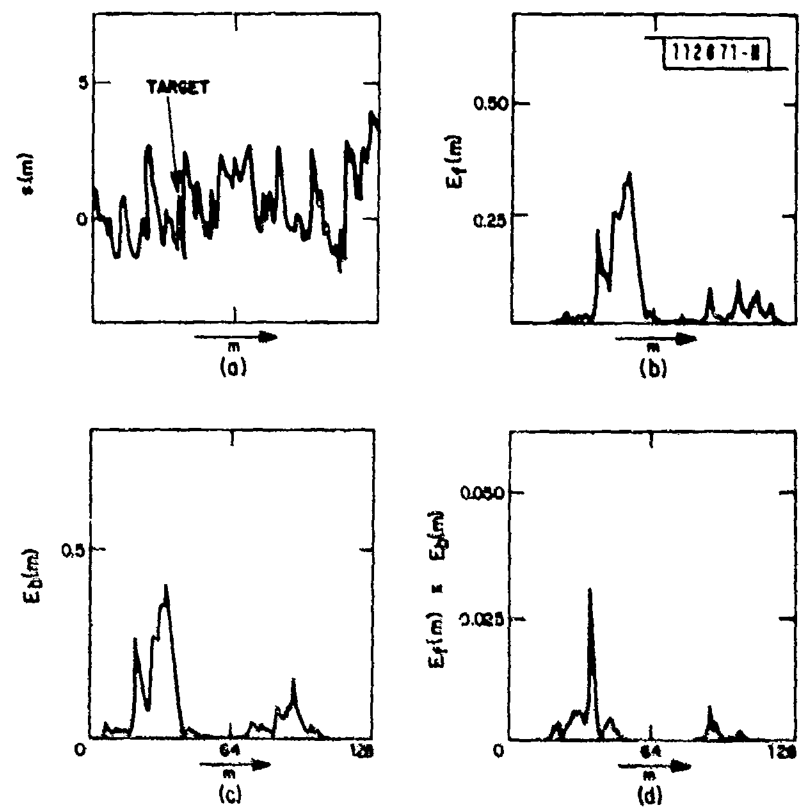

Fig. 5. Detection of a 1-point target by RLS: (a) a sequence s(m) representing background and target, (b) forward error [denoted by $E_f(m)$], (c) background error [denoted by $E_b(m)$], and (d) product $E_f(m) \times E_b(m)$.

REFERENCES

1. Multi-Dimensional Signal-Processing Research Program Semiannual Technical Summary, Lincoln Laboratory, M.I.T. (31 March 1981).
2. M. Ekstrom and J. Woods, "Two-Dimensional Spectral Factorization with Applications in Recursive Digital Filtering," IEEE Trans. Acoust., Speech, and Signal Processing ASSP-24, 115-127 (1976).
3. A. S. Willsky, "A Survey of Design Methods for Failure Detection in Dynamic Systems," Automatica 12, 601-611 (1976).
4. W. P. Dove and A. V. Oppenheim, "Event Location Using Recursive Least Squares Signal Processing," IEEE Intl. Conf. on Acoustics, Speech, and Signal Processing, Denver, Colorado, 9-11 April 1980.
5. K. J. Astrom and P. Eykhoff, "System Identification – A Survey," Automatica 7, 123-162 (1971).

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